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Research Paper

The recognition of litchi clusters and the calculation of picking point in a nocturnal natural environment

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In a natural environment, the recognition of ripe litchi and calculation of the picking point are always difficult problems for a picking robot. In this study, a visual system for litchi image acquisition is built and a method of nocturnal litchi recognition and a calculation of picking point is proposed. For comparison, images of the same cluster of litchis are captured during the day in a natural environment and during the night using artificial illumination. By analysing colour features of the same litchi image in different colour models, the YIQ colour model is proved to be the model with the best practicability for nocturnal litchi recognition. In this proposed method, the background of the nocturnal image, instead of the litchi fruit and stem, is first removed using an improved fuzzy clustering method (FCM) combining this analysis approach with a one-dimensional random signal histogram. The fruit is then segmented from the stem base using the Otsu algorithm. The Harris corner was used for picking point detection. The change rates of the horizontal and vertical positions between corner points are analysed to identify the picking point. The experiments show that nocturnal litchi recognition accuracy is 93.75% with an average recognition time of 0.516 s. At different depth distances, the highest accuracy for the picking point calculation is 97.5%, while the lowest is 87.5%. The results show the accuracy and feasibility of this method for litchi recognition and picking point calculation during the night. This research provides technical support of visual localisation technology for litchi-picking robots.

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1. Introduction

With the rapid development of computerised and automated control techniques, picking robots are now gradually penetrating into agricultural production (Bac, Hemming, & van Henten, 2014). It is of great application value and realistic importance to improve agricultural productivity by developing intelligent picking robots of fruits and vegetables using computer vision. Both fruits and vegetables are living

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Nomenclature

Symbols

d	distance from the right intersection to the left
h	horizontal height from the lowest Harris corner of the stem
δ	the ratio of d_{max} to d_{min}
h_y	Y-values of the picking point, the minimum of h in curves
$g(x)$	a one-dimensional Gaussian function
σ	standard deviation of normal distribution
μ	expectation of the Gaussian distribution
$I(x)$	the histogram of I component of a nocturnal image
$\varphi(x)$	convolution result of a one-dimensional histogram $I(x)$ using the Gaussian function
$\varphi'(x)$	first order difference calculation of the convolution result $\varphi(x)$
$\varphi''(x)$	second order difference calculation of the convolution result $\varphi(x)$
$\{x_i\}$	set of values where $\varphi'(x_i) = 0, \varphi''(x_i) < 0$
c	the cardinal number of $\{x_i\}$
Δd	one-tenth of the difference between d_{max} and d_{min}

Abbreviations

YIQ	YIQ colour space; Y is Luminance, I is In-phase, and Q is Quadrature-phase
FCM	Fuzzy C-means clustering algorithm
EA	Exploratory Analysis
RGB	Red, Green and Blue colour model
HSV	HSV colour model; H is hue, s is saturation, and v is value
Lab	Lab colour space; L is lightness and a and b are the colour opponents green–red and blue–yellow
YUV	YUV colour space; Y is the luma component (the brightness), U and V are the chrominance (colour) components

organisms with variability in sizes or shapes and random distribution in a tree. Precise spatial localisation to target fruits is the key to implementing robotic fruit picking (Xiang, Jiang, & Ying, 2014). Machine vision technology is always applied to the target localisation of picking robots with two types of difficulties, including accurate recognition of the fruit and the picking point calculation. Therefore, precise visual localisation becomes the key technology in research of fruit-picking robots (Zou et al., 2016). A picking robot usually works in an unstructured natural circumstance with many types of random factors that make it difficult to implement precise localisation (Berenstein, Shahar, Shapiro, & Edan, 2010).

Some related research has been done in recent years. For instance, Slaughter & Harrell (1987) used the chroma and luminance of orange images captured under natural light to guide an orange harvesting manipulator. Their classification model for oranges on a tree was built based on colour information. The orange classification accuracy rate was 75%, and the error rate of orange shape recognition was 6%. This research verified the practicability of visual localisation for robots in a natural environment. Kondo, Shibano, Mohri, and Monta (1994) developed a tomato-picking robot using a colour camera to build a visual localisation system. Ripe tomatoes were taken as the research object and the picking success rate was approximately 70%. The picking error was mainly caused by wrong localisation owing to environmental factors. Ceres et al. (1998) attributed the recognition fault using an optical camera to the changeable natural light and a similar colour or shape between fruit and background. They proposed a method of using a laser area detection sensor to obtain an image and detect the fruit based on shape. Artificial trees and real trees were tested. Approximately 80% of visible fruits were detected without any false recognition. Bulanon and Kataoka (2010) used the LCD (Luminance and Colour Difference of red) model to conduct threshold segmentation and recognition of Fuji apples on the basis of the large difference between the apple's colour and the background. The recognition accuracy was 88%, and the error rate was 18% in backlit circumstances. By installing a colour CCD camera on the end-actuator, an apple-picking robot could recognise and orient the apples (De-An, Jidong, Wei, Ying, & Yu, 2011). The results from the laboratory and outdoor-picking experiments showed a success rate of 77%. From this research, we have learned that visual localisation of a picking robot can be disturbed by various natural factors, especially the recognition and localisation error caused by natural illumination. Therefore, some visual technology studies of picking robots were conducted in a greenhouse environment. Jiang, Peng, and Ying (2008) conducted localisation research of tomato and citrus in the greenhouse. The binocular stereo visual technology was used to obtain the 3D position of the fruit and vegetable. The results showed that in both front lighting and backlighting circumstances, the recognition model could identify the citrus with a higher success rate. By analysing the spectral characteristics of cucumber and its leaves, the difference in spectral characteristics was used to recognise cucumber by a greenhouse picking robot (Yuan, Li, Qingchun, & Zhang, 2010), with a recognition rate of 83.3%.

The influence of natural light on visual recognition in a greenhouse is diminished but not avoided. For this reason, some researchers have proposed nocturnal visual technology research on picking robots. Liu et al. (2016) designed a nocturnal experiment for apple picking, in which colour information of RGB and HIS mode images were used as training samples for a BP neural network to segment the apples from the images. The Euclidean distance was applied to further calculate the edge area, and the target apple area was finally determined. Recognition accuracy of apples in a natural environment can be improved using this method. However, a high recognition error rate occurs when apples are overlapping or a shadow occurs in captured images. Fu et al. (2015) proposed a nocturnal kiwi fruit visual recognition system using artificial illumination and colour information of an R–G mode image for recognition, and an accuracy rate of 88.3% was achieved. Payne, Walsh, Subedi, and Jarvis (2014) proposed a quality detection system for mangos on trees using visual technology and artificial illumination, in which a hybrid

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